



# Estimation of the spatial climate comfort distribution using tourism climate index (TCI) and inverse distance weighting (IDW) (case study: Fars Province, Iran)

Malihe Masoudi<sup>1</sup>

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## Abstract

This article was conducted to perform a temporal and spatial analysis in order to identify suitable climatic regions for tourism. We investigated tourism climate conditions in Fars province from 2006 to 2016 using tourism climate index (TCI). Also, modified inverse distance weighting (IDW) interpolation is applied to generate the optimal spatial pattern of the TCI distribution. The relationship between the interpolation accuracy and a critical IDW parameter, called power value ( $\beta$ ), was evaluated for optimization. The results revealed that during four months of May, April, October, and November, 70–83% of cities in Fars province show excellent and ideal climatic comfort. In the four months of July, December, January, and March, about 45–54% of Fars province provide good and very good conditions for tourism activities. The spatial distribution of TCI also shows that the cities in the northern part generally have the most desirable conditions during the hot season, while the southern cities of Fars province are more suitable for tourism during the cold season. Also, analysis of optimization steps demonstrated that power value ( $\beta$ ) affects interpolation accuracy. As our study suggests, using the optimal power values ( $\beta$ ) of 1 and 2 can lead to optimal spatial interpolation of the TCI distribution. Overall, we found IDW and TCI as reliable tools for assessing bioclimatic comfort conditions, considering  $\beta$ -value as an influential factor that should be evaluated to achieve optimal interpolation results.

**Keywords** Bioclimatic comfort · IDW · Optimized spatial pattern · Power value ( $\beta$ )

## Introduction

Today, tourism, as a dynamic and widespread industry, encompasses all the essential elements of a global society and system (Dávid 2010; Mohammadi et al. 2009). Considering the importance of tourism and its role in economic development (Csorba 2003), it is essential to recognize the factors that influence tourism. Environmental parameters play an important role in tourism development (Pérez 2009), as do other factors such as cultural, social, and political factors. These environmental parameters include biological and natural factors (climate, geology, topography, fauna and flora) and also some factors created

by human activities (Barczi et al. 2008), in particular land-use changes (Demény and Centeri 2008; Centeri et al. 2012) and landscape (Renes 2018) or scenery (Kruse and Paulowitz 2018). Climate resources are one of the most important factors for the development of the tourism industry (Bigano et al. 2007; De Freitas et al. 2008; Mohammadi et al. 2009; Cetin 2015), influencing the choice of destinations by tourists (Dogru et al. 2016). Climate is considered an important factor in choosing the destination by assessing the time of year when climatic conditions are optimal, or by determining a region that offers the most desirable climatic conditions. Eventually, it influences tourists' satisfaction with the location of the destination, the state of thermal comfort, and the climatic comfort of tourists (Kovács and Unger 2014).

Bioclimatic comfort means that a person feels comfortable under the conditions of the natural environment (Lin and Matzarakis 2007; Andamon et al. 2006; Cetin et al. 2018; Wu et al. 2020). There are several climatic variables that can influence climate comfort condition. According to Olgyay (2015), the best bioclimatic comfort values are a temperature of 21 to 27.5 °C and relative humidity of 30 to 65% (Cetin

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✉ Malihe Masoudi  
Masoudi.Malihe@phd.uni-mate.hu; masoudim65@gmail.com

<sup>1</sup> Faculty of Agricultural and Environmental Sciences, Institute of Nature Conservation and Landscape Management, Hungarian University of Agricultural and Life Sciences, Páter K. u. 1, Gödöllő 2100, Hungary

2015). In addition to temperature and relative humidity, two other elements, wind speed, and radiation, play an important role in creating human comfort conditions (Topay and Yilmaz 2004; Blazejczyk 2001; Bazrpash et al. 2011; Ahmadi and Ahmadi 2017; Wu et al. 2020). For this reason, most climate comfort models are based on these parameters. Thermal indices are one of the most common methods for studying climate comfort, often used to assess tourism climate and determine climate capacity in different regions. Several studies have used different thermal indices to assess tourism climate in the world (e.g., Mieczkowski 1985; Hartz Donna et al. 2006; Zengin et al. 2010; Kovács and Unger 2014; Kovács et al. 2017; Hassan et al. 2015; Yushina and Yegemberdiyeva 2019; Masoodi et al. 2016; Mahmoud et al. 2019; Haryadi et al. 2019; Noome and Fitchett 2019).

The tourism climate index (TCI) proposed by Mieczkowski (1985) is one of the most effective and applicable thermal indicators (De Freitas et al. 2008; Mubarak Hassan et al. 2015), which has been widely used to assess the climatic suitability of tourist destinations due to the large number of parameters it contains (Scott et al. 2016). For example, Hejazizadeh et al. (2019) conducted a comparative assessment of human bioclimatic in the Iranian coast of Makran using HCI and TCI methods. They compared two indices and found that TCI has a wider range from unfavorable to favorable conditions throughout the year. In another study, Farajzadeh and Ahmadabadi (2010) evaluated climate tourism in Iran using TCI; also, Arvin et al. (2013) evaluated climate conditions of Fars province using PET and PMV. Cheng and Zhong (2019) also evaluated the climate conditions of tourism in the Grand Shangri-La (GSL) region (China) from 1980 to 2016 using the tourism climate index (TCI). In addition to temporal analysis, spatial analyses must be considered when planning tourism development. Drawing maps for the spatial distribution of tourism climate can help in identifying vulnerable areas. Fortunately, the Geographic Information System (GIS), which is a powerful spatial analysis tool, provides a practical and relevant working environment and effective technique for the integration of different datasets (Abuzied 2016; Abuzied et al. 2020; Dobesch et al. 2013). It also has been widely used for the evaluation and visualization of different natural resources (Abuzied and Alrefae 2017). Spatial interpolation is a method of generating continuous data collected at different locations (points) and has been regularly used to distribute climate data (Kim et al. 2010; Chen and Liu 2012; Yang et al. 2015; Pellicone et al. 2018; Wu et al. 2020). These methods have the advantage of being objective, the results are reproducible, and they effectively manage large data sets. Automated interpolation methods specifically reconstruct surfaces as a function of coordinate position ( $x, y$ ) and a set of known control values. Inverse distance weighting (IDW) is one of the most popular interpolation methods widely used for the distribution of climate comfort conditions (Attorre et al. 2007; Sari et al. 2010;

Hashidu et al. 2017; Yezhi et al. 2019). It is known as a statistical interpolation method commonly used by geoscientists (Bartier and Keller 1996) and has been implemented in different GIS packages (Maleika 2020). However, the result of the IDW interpolation method can be affected by 2 factors. The first is the distance between the known points to the unknown points; the second is proportional to the inverse distance (between the data point and the prediction location) raised to the power value  $\beta$  (Chen and Liu 2012).

Considering Iran's tourism potential in terms of ecological nature, climatic diversity, geography, biodiversity, and cultural attractions, the country ranks only eighth in the world's tourism rankings, and its average tourism GDP is only 0.04% (Soleimani and Moghise 2010). Therefore, it is crucial to identify the country's tourism capabilities and present them to tourism practitioners. The focus of most studies conducted in this regard in Iran is on the point state rather than the spatial scale. They mostly calculated comfort conditions for stations and then assigned them to other areas, for example, using isopleth maps (Arvin et al. 2013), which are not as precise as interpolation maps. Therefore, the main objective of this study is to perform a spatio-temporal analysis in the search for suitable climatic regions for tourism using GIS and comfort index. Fars province was chosen as a case study because of its rich natural potential and attractiveness that can be a solution for job creation, economic and human development, and other economic sectors if deliberately planned. Also, to generate optimal interpolation maps, we evaluated the optimal power or  $\beta$ -value (corresponding to the GIS standard range) to obtain optimal interpolation results.

## Material and method

### Case study

Fars province is one of the 31 provinces of Iran; it is located in the southwest of the country and is the fourth largest province with an area of approximately 122,608 km<sup>2</sup>. Due to the different landscapes, this province has many different climatic zones. Based on the classification method of De-Martonne, Fars province has five climate types including arid, semi-arid, dry, Mediterranean, semi-humid, and humid (Deihimfard et al. 2015), which show the capacity of climate variations in the province. In this study, data from 24 synoptic stations during the statistical period, 2006–2016, were used. The data used are the climatic norms calculated by the Iranian Meteorological Organization, which are obtained from the database of the meteorological bureau of Fars province. The data quality control was performed by the department, but the conventional method of data reconstruction and validation (Simple Arithmetic Averaging) was used in rechecking the

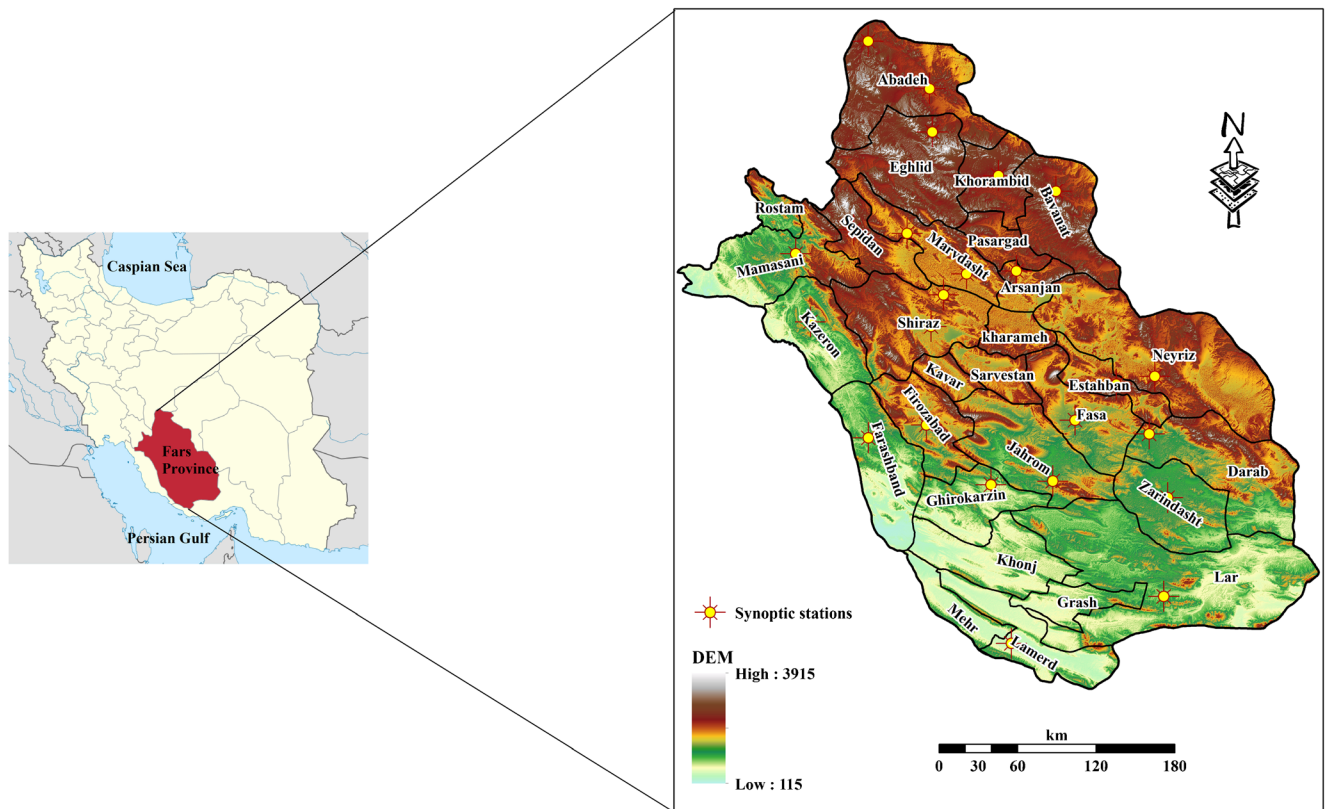


Fig. 1 Study area in the south of Iran and distribution of studied stations

data for the same statistical periods. Figure 1 shows the study area and location of synoptic stations in Fars Province.

### Methodology

#### TCI

The tourism climate index (TCI) systematically assesses climatic conditions for tourism using 7 parameters which include the following: average monthly rainfall, average temperature,

average relative humidity, maximum temperature, minimum relative humidity, average daily sunshine duration, and wind speed. This index provides information about the weather conditions of the destination at different seasons. Therefore, tourists can choose a travel time with optimal and favorable weather conditions (Mieczkowski 1985). The main tourist activities considered in this index are sightseeing and shopping. Table 1 shows the main components of the TCI and its impact on tourism.

Each of the 5 components listed in Table 1 is rated on different scales from 0 (unfavorable) to 5 (optimal) while the

Table 1 Sub-indices within the tourism climate index, their impact (based on Scott and McBoyle 2001)

Subindex	Monthly climatic variable	Effect on tourism	Score	Weight (%)
Daytime comfort index (CID)	Mean of the max of temperature, mean of min of humidity	Shows the thermal comfort when tourists are most active	-3 to +5	40
Daily comfort index (CIA)	Mean daily temperature, mean of humidity	Shows the thermal comfort throughout the night and day, which is even bedtime	-3 to +5	10
Precipitation index (P)	Monthly precipitation sum (mm)	Reflects the adverse effects of precipitation on the holiday fun	0 to +5	20
Sunshine duration index (S)	Daily sunshine duration (hour)	Considered good for tourism and the other side has a bad effect on the risk of sunburn and discomfort on hot days	0 to +5	20
Wind speed index (W)	Daily mean wind speed (km/h)	The wind effect depends on the temperature. The cooling effect of the wind is good in warm climates the cooling effect of the wind is bad in cold climates	0 to +5	10

thermal comfort sub-indices (CID and CIA) get the rate from -3 to 5. Each of these five components contains a portion of the final coefficients. The daytime comfort index (CID) is the most important influential factor for a region’s tourist climate, with 40% weight. It is determined by the combination of the two factors of maximum dry temperature and minimum relative humidity (ALDabbas et al. 2018) using the effective temperature index curve (Fig. 2). Also, the CIA is calculated in the same way and by considering two elements of average temperature and average relative humidity. Precipitation (P), radiation (S), and wind speed (W) are also presented by Mieczkowski (1985). The final coefficient of the tourism climate is extracted from the sum of the coefficients of these 5 components and by using eq. 1 (Mieczkowski 1985).

$$TCI = 2[(4 \times CID) + CIA + (2 \times P) + (2 \times S) + W] \quad (1)$$

Finally, the explanatory value of TCI is obtained from Table 2.

**IDW interpolation**

Since the values of the TCI for the studied stations are point-based, it is necessary to generalize the point data to the area for mapping and interpolating TCI values. There are several interpolation methods for this purpose. The number of samples (observations) plays an essential role in choosing the best technique. In our case, because of the small number of stations (24 stations), we have chosen the method of inverse distance weighting (IDW). Also, there are other benefits to this method. This method is known as one of the most widely used and successful techniques among interpolation methods. It is fast, easy to implement, and can be easily modified for specific requirements. Moreover, this approach allows for anisotropy in the data (Sluiter 2009).

IDW estimates cell values by averaging the values of sample data points near each processing cell. It assumes that each

**Table 2** The explanatory value of TCI index (Mieczkowski 1985)

Score of TCI	The explanatory value of TCI
90–100	Ideal
80–89	Excellent
70–79	Very good
60–69	Good (well)
50–59	Acceptable
40–49	Acceptable (little)
30–39	Unsuitable
20–29	Very unsuitable
10–19	Extremely uncomfortable
-30–9	Impossible

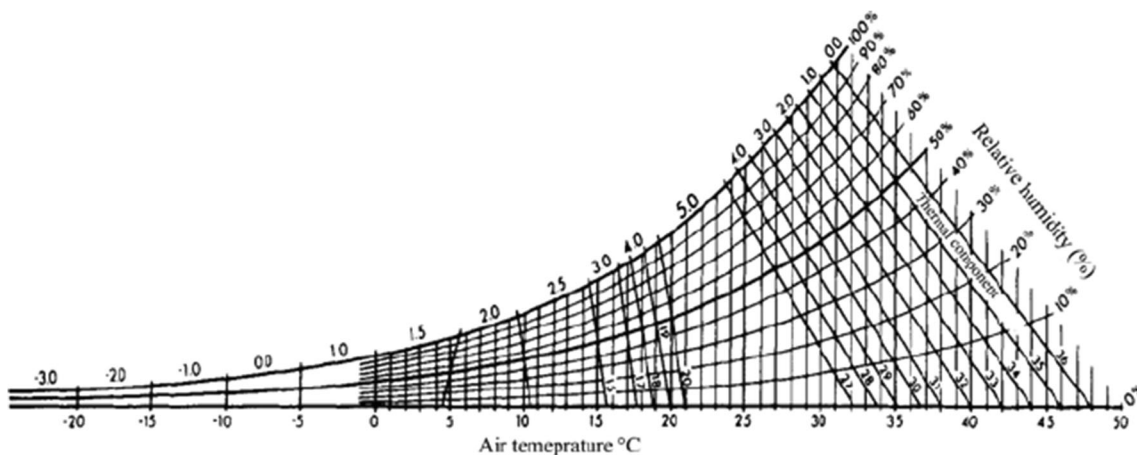
measured point has a local influence that decreases with distance (Chen and Liu 2012). The points closest to the prediction location are weighted more heavily, and the weights decrease with increasing distance.

The general equation for IDW is (Bartier and Keller 1996):

$$x = \frac{\sum_{i=1}^n z_i w_i}{\sum_{i=1}^n w_i} \quad (2)$$

where  $x$  is the point to be estimated,  $Z_i$  represents the control value for the  $i$ th sample point, and  $W_i$  is a weight that defines the relative importance of the individual control point  $Z_i$  in the interpolation procedure. As a binary switch,  $W_i = 1$  for the  $n$  control points closest to the interpolated points, or for the set of control points within a certain radius  $r$  of the point to be interpolated; otherwise,  $W_i = 0$ . An alternative weighting strategy, which gives near points relatively more influence than far points, is based on the reciprocal of power in relation to distance, such that:

$$W_i = d^{-\beta}_{x,y,i} \quad (3)$$



**Fig. 2** Thermal comfort classification of tourism climate comfort index based on the effective temperature index (Mieczkowski 1985)



where  $d_{x,y,i}$  is the distance between  $z_{x,y}$  and  $z_i$  and  $\beta$  is an exponent defined by the user. Therefore, Eq. (4) can be rewritten as:

$$X_{yz} = \frac{\sum_{i=1}^n Z_i d_{x,y,i}^{-\beta}}{\sum_{i=1}^n d_{x,y,i}^{-\beta}} \tag{4}$$

$\beta$  means potency (power) and is also a control parameter generally assumed to be two, as used by Zhu and Jia (2004) and Lin and Yu (2008), or six, as defined by Gemmer et al. (2004).

In this study, we evaluated the relationship between prediction accuracy and  $\beta$ -value. For this purpose,  $\beta$ -value is conducted in the range of 1 to 3 (Esri 2011), with an incremental interval value of 1. Ultimately, RMS was used to determine the optimal power ( $\beta$ -value) parameter (Table 3).

### Cross-validation

Cross-validation is essential to assess the performance of the interpolation method and validate the results.

Cross-validation involves using all the data to predict patterns and autocorrelation models. We applied the Leave-One-Out Cross-Validation (LOOCV) technique to evaluate the performance of the spatial interpolation method. In this strategy, each data location is removed individually and its value is re-estimated from the remaining dataset using interpolation (Sanabria et al. 2013). Accuracy is determined by calculating the RMS error and the mean error (ME) between observed and modeled values in all stations (Eqs. 5 and 6). Besides, we used basic statistics including the mean absolute error (MAE) and correlation coefficient ( $r$ ) (Eqs. 7 and 8) to assess whether the estimated data are consistent with the observed data (Chen and Liu 2012; Wang and Lu 2018).

$$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^n [Z^*(X_i) - Z(X_i)]^2} \tag{5}$$

$$ME = \frac{\sum_{i=1}^n [Z^*(X_i) - Z(X_i)]}{n} \tag{6}$$

$$MAE = \frac{\sum_{i=1}^n |Z^*(X_i) - Z(X_i)|}{n} \tag{7}$$

$$r = \frac{\sum_{i=1}^n (Z(X_i) - \bar{Z}_i) (Z^*(X_i) - \bar{Z}_i^*)}{\sqrt{\frac{1}{n} \sum_{i=1}^n (Z(X_i) - \bar{Z}_i)^2 \sum_{i=1}^n (Z^*(X_i) - \bar{Z}_i^*)^2}} \tag{8}$$

where  $z^*(xi)$  is the estimated value at location  $i$ ,  $z(x_i)$  is the actual value at location  $i$ , and  $n$  is the number of data.

### Results and discussion

The relationship between climate and tourism demand has long been discussed in the tourism industry (Scott et al. 2011; Ruddy et al. 2020). That not only influences the suitability of a region for different types of recreational activities but is also necessary for the seasonality of many tourism destinations (Perch-Nielsen et al. 2010). Generally, climate comfort indices are applied to assess the climate comfort condition of the regions. To date, most climate tourism indices have produced simplistic and one-sided (e.g., Becker 1998). However, some climate comfort indices contain a large number of parameters for assessing climatic suitability. TCI is known as one of the most comprehensive indexes developed in the last 35 years (Mieczkowski 1985; Harlfinger 1991; Morgan et al. 2000).

In this study, climatic conditions of tourism in Fars province were evaluated using TCI for each month. Table SII presents TCI results for all months. Figure SII also shows the trend of the index per month at different stations. The station numbering is such that station 1, locates in the northernmost part of the study area, and station 24 is in the southernmost part of the study area. Figure 3 presents the distribution of TCI in 24 stations.

After determining the TCI value for each station, the IDW interpolation method was applied for spatial analysis and the distribution of the TCI all over the Fars province. To obtain more accurate interpolation results, we evaluated different power values ( $\beta$ ). Finally, with the comparison of determined RMS, it is revealed that the power values of 1 and 2 are more suitable for interpolation in this study (Table 3). Also, Fig. 4 shows the distribution or optimal spatial pattern of tourism comfort conditions in all cities during each month.

**Table 3** comparison of different  $\beta$  based on RMS

	$\beta$	April	May	June	July	August	September	October	November	December	January	February	March
RMS	1	6.4	10.4	11.7	13	11.7	12.1	8.4	7.5	8	8.2	7.3	6.3
	2	6.5	9.5	11.4	12	11.3	11.3	7.9	7.2	8.2	8.4	6.9	5.9
	3	6.8	9.8	11.4	12.7	11.5	11.4	8.2	8.6	8.4	8.6	6.7	6.1

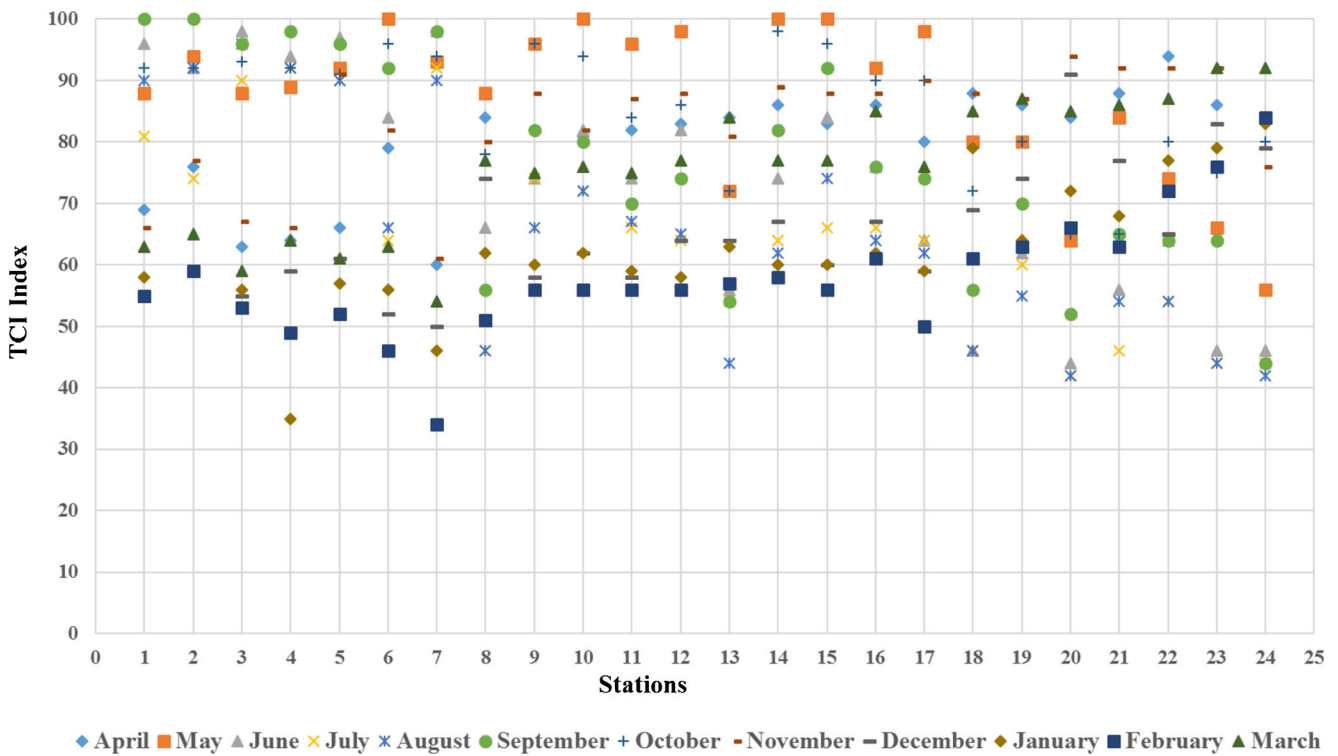


Fig. 3 Distribution of the climate tourism index in 24 stations in the Fars province for 12 months

The TCI results show that the weather in April and May varies from good to great and infinite at all stations (Fig. 3). During the mentioned months, the cities of Estahban, Takht-e-Jamshid, Doroodzan Dam, and Neyriz show extremely good conditions (TCI=100) (Table SII). In June, climatic conditions show favorable (good to ideal) state in most of the cities except Ghirkarzine, Lamerd, Larestan, and Farashband which are in marginal conditions. In July, also the cities of Darab, Farashband, Larestan, Lamerd, Nourabad, and Ghirkarzine showed marginal conditions, and acceptable conditions are observed in Kazeroon and Zarrindasht while other cities are in good to ideal states, besides poor and marginal conditions are seen in Farashband, Kazeroon, Larestan, Lamerd, Nourabad, and Ghirkarzine. August shows acceptable conditions in Zarrindasht, Darab, and Jahrom, while in September infinite conditions prevail in the cities of Izdakht and Abadeh, marginal conditions also prevail in Lamerd, and acceptable conditions are observed in Farashband, Kazeroon, Nourabad, and Ghirkarzine. The other towns are in perfect condition (Fig. 4).

Based on the results for October and November, all cities show good to ideal conditions. December also shows good conditions in most cities except Sepidan, Abadeh, Firouzabad, Safashahr, Droodzan Dam, Zarrin Dasht, Izadasht, Eghlid, and Arsanjan. These cities have only acceptable climatic conditions in December.

Conditions in most cities are in the acceptable range, during the early winter months, except for Safashahr and Sepidan, which are in poor and borderline range. February also shows very good to excellent conditions in some cities like Lamerd, Larestan, Ghirkarzine, and ZarinDasht, while the situation in the other parts varies from poor to borderline. In the end, acceptable and excellent conditions are observed in March in most districts of the province.

Based on the results, it is evident that the values of TCI and its components vary in different cities of the Fars province. This climatic diversity has led to the formation of favorable zones for winter and summer tourism in the study area. According to Fig. 3, the lowest values (unsuitable condition) occur at stations 7 and 4 in February and January. Also, stations 1 and 2 in September and stations numbers 6, 10, 14, and 15 in May get the highest TCI values (ideal condition). Moreover, stations of 1, 2, 5, 9, 10, 11, 12, 14, 15, and 16, which are mainly in the north and center of the study area, have current values above 50 (acceptable to ideal). Overall, the whole parts of Fars province offer favorable conditions in April, May, October, and November. According to the spatial pattern of climatic comfort conditions (Fig. 4), the southern cities and stations such as Lamerd, Larestan, Khonj, Zarrin dasht, and Ghirkarzine are more favorable for tourism in the

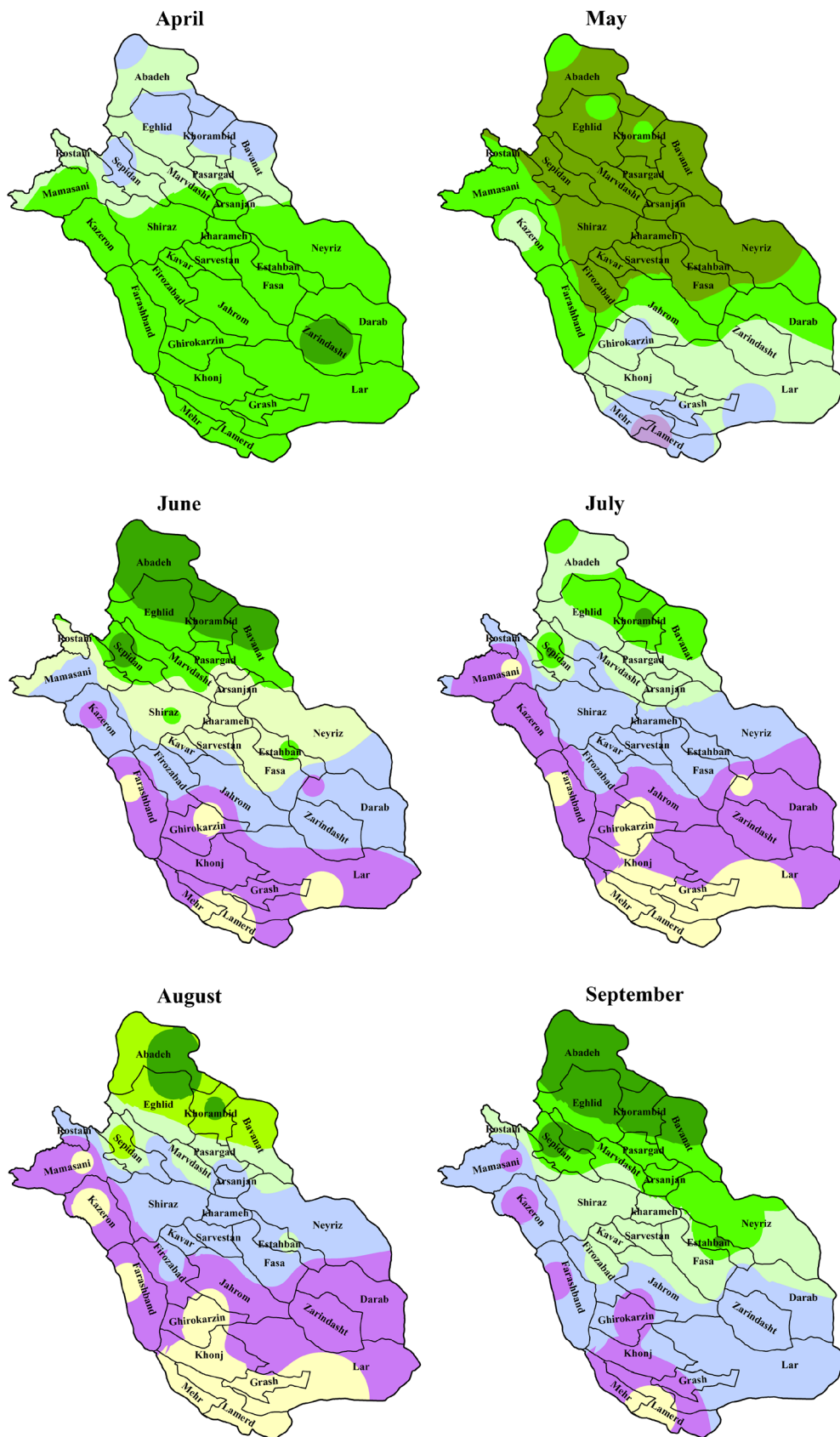


Fig. 4 The tourism climate condition distribution in Fars Province

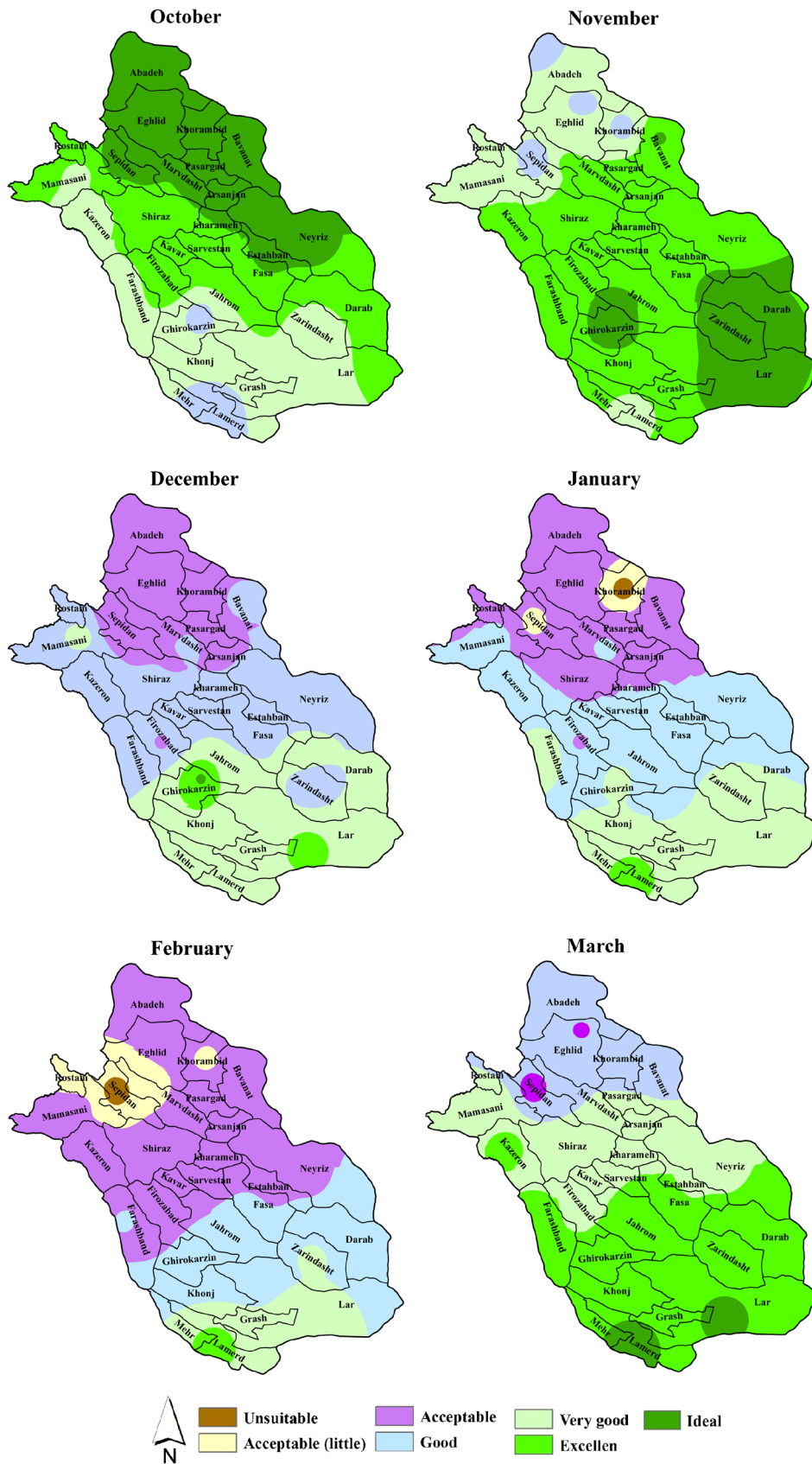


Fig. 4 (continued)



**Table 4** Summary statistics between the measured and predicted value

Month	ME	RMS	<i>r</i>	MAE
April	0.11	6.4	0.65	3.5
May	3.6	9.5	0.69	3.07
June	1.9	11.4	0.79	5.8
July	1.2	12	0.65	5.8
August	1.5	11.3	0.78	5.35
September	1.5	11.3	7.6	4.9
October	1.6	7.9	0.63	2.6
November	0.5	7.2	0.54	4.1
December	-1.1	8	0.57	3.9
January	-1.444	8.2	0.6	3.7
February	-1.4	6.7	0.75	2.97
March	-0.8	5.9	0.83	3.1

cold season, and the northern cities such as Eglid and Abadeh offer more favorable conditions in the hot summer season. These results are consistent with the general findings of Bakhtiari et al. (2018) and Farajzadeh and Ahmadabadi (2010), which present the TCI distribution throughout the country of Iran. This pattern is also consistent with the result of Arvin et al. (2013). They used different methods (physiologically equivalent Man Ray temperature (PET) and mean survey prediction (PMV)) to determine the climate conditions in Fars province and the same temporal pattern as our study.

Moreover, the IDW interpolation approach is applied to determine the spatial pattern of climatic comfort conditions. Here, we evaluated the relationship between interpolation accuracy and a critical parameter of IDW called power ( $\beta$ -value) to obtain the optimal interpolation maps. We examined values in the range of 1–3 that is suggested by GIS. The results showed that values of 1 and especially 2 have a better impact on the interpolation accuracy. Zhu and Jia (2004) and Lin and Yu (2008) had the same results in their studies. Therefore, the final interpolation maps were performed based on these power values. The spatial patterns resulted from IDW showed the well-known spatial phenomenon of TCI, where the comfort conditions almost decrease in the hot season and increase in the cold season from north to south. This phenomenon is consistent with the spatial patterns resulted from PMV and PET index used by Arvin et al. (2013). It is also consistent with the result of Ahmadi and Ahmadi (2017) study that used the geostatistical interpolation method for mapping.

To evaluate the performance of the interpolation method, we used Leave-One-Out Cross-Validation to validate the results (Fig. 5). In addition, basic statistics including the mean absolute error (MAE) and the

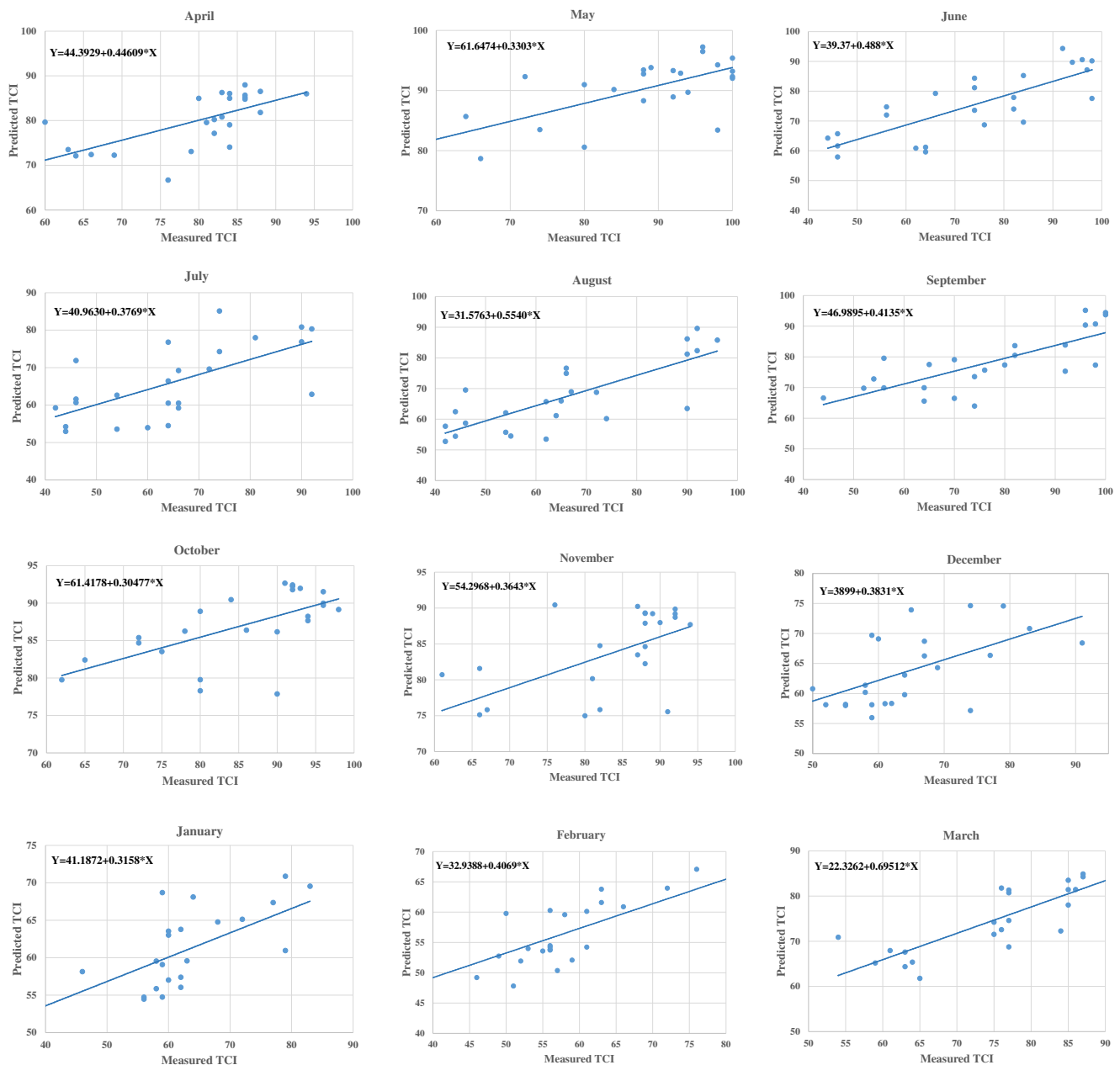
correlation coefficient (*r*) were used to assess whether the estimated data is consistent with the observed data and to evaluate the reliability of IDW. Table 4 presents a summary of the basic statistics (*r* and MAE) and the cross-validation (ME and RMS) results.

The cross-validation results (Fig. 5) and the specially obtained basic statistic *r* show that a relatively strong correlation is between the observed and estimated values (Table 4) which confirms the reliability of IDW interpolation in this study. Also, the comparison of RMS value between different months shows that the prediction accuracy is better in the rainy season (October to April) than in the dry season (May–September) (Table 4). Thus, it can be concluded that IDW has significant predictive power at lower values than at higher values.

## Conclusion

In this study, we analyzed the variability of climate comfort conditions in Fars Province. We have also generated the spatial distribution of the climate comfort index using IDW, which leads to identifying the vulnerable areas. The results revealed that in 10 months of the year, Fars Province has enough bioclimatic comfort conditions (slightly acceptable to ideal) for tourists. As in the four months of May, April, October, and November, 70–83% of the cities have excellent to ideal climatic comfort conditions, also in the four months of July, December, January, and March, 45–54% of the whole province provide good and very good conditions for tourism. According to the spatial distribution of TCI, the cities located in the north part of the Fars province generally have the most desirable conditions during the hot season, while the southern cities of Fars province are more suitable during the cold season. Also, April and May are known as the best months, with good to excellent conditions throughout the study area. The analysis of the maps showed that 8.8% of the seasons had severe climate conditions.

IDW results also show more accurate results in the rainy season (October to April) than in the dry season (May–September), which means that IDW has significant predictive power at lower values than higher values. It should be noted that IDW cannot make the estimation above the maximum or below the minimum values, which is known as one of the weaknesses of this method. Based on the cross-validation results and the observed significant correlation coefficient between estimated and observed data, we finally confirmed IDW as a reliable spatial interpolation method for predicting climate comfort in Fars province. Moreover, through the



**Fig. 5** Cross-validation of IDW interpolation for TCI at 12 months

analysis of optimization steps, the power value ( $\beta$ ) of influence should be considered an effective factor affecting the accuracy of IDW results. Overall, we found IDW and TCI as reliable tools for assessing bioclimatic comfort conditions that can be used in other locations, considering  $\beta$ -value that should be evaluated to achieve optimal results. Also, it should be noted, due to the climatic comfort achieved for Fars Province, improving the recreational and tourism role of this region can be one of the most productive and efficient economic sectors of the province. These results should be noted by the administration to achieve better development of the tourism industry in Fars province.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s12517-021-06605-6>.

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**Data availability** The author declares that the data used in this manuscript are freely gained from synoptic stations of the case study. <http://www.farsmet.ir/Default.aspx>

**Declarations** This manuscript has neither been published nor is currently under consideration by any other Journal.

**Conflict of interest** The author declares no competing interests.

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